

# Developing Exposure-Response Relationships for Annoyance Caused by Vibration from Freight and Passenger Railway Traffic

Calum J. Sharp  
James Woodcock  
Gennaro Sica  
Eulalia Peris  
David C. Waddington  
Andrew T. Moorhouse  
Acoustics Research Centre, University of Salford, Salford, UK.

## Summary

The aim of this paper is to apply a new categorisation algorithm to an existing database of case studies in order to investigate its effectiveness in sorting unknown train vibration signals into freight and passenger train categories for exposure-response analysis. Relatively little work has been performed on the human response to vibration from railway transportation when compared with response to air-borne noise. Data for this work comes from case studies comprising face-to-face interviews and vibration measurements collected within the University of Salford study "Human Response to Vibration in Residential Environments". There are indications within this database that the annoyance response due to freight and passenger trains may be significantly different. The novelty of this work, therefore, is the use of an algorithm that separates freight and passenger train vibration signals in order to further analyse the exposure-response relationships due to passenger trains and freight trains separately. This is achieved by analysing the individual vibration signals and separating them based on signal properties that are shown to be significantly different for passenger and freight trains. Initial estimates of exposure response relationships are then constructed using ordinal probit modelling. Initial exposure response-relationships developed using data categorised by the algorithm are presented and the relative success of this method is discussed. The implications of these findings for the potential expansion of freight traffic on rail are discussed. [Work funded by the Department for Environment, Food and Rural Affairs (Defra) UK, and EU FP7 through the CargoVibes project]

PACS no. 43.40.+s, 43.66.+y

## 1. Introduction

European rail operators intend to increase their market share of goods traffic from 8% in 2001 to 15% in 2020 and so will be relying much more heavily on freight railway transport [1]. Research has shown that increasing levels of transport noise and vibration can induce annoyance and sleep disturbance [2, 3]. It has also been shown that annoyance due to vibration is higher at night than during the day, and that annoyance reactions due to noise occur more frequently during the evening and night-time, when freight railway traffic tends to be more prevalent [4, 5]. There is there-

fore a need to better understand the human response to railway noise and vibration, so that measures to ensure acceptable combined levels of noise and vibration can be developed, minimising the degree of annoyance and sleep disturbance experienced by residents located in the vicinity of freight railway lines.

The University of Salford has recently completed a research project funded by the Department for Environment, Food and Rural Affairs (Defra, UK), which was successful in determining exposure-response relationships for annoyance caused by vibration from railway traffic [6]. These relationships show the proportion of respondents that are likely to be slightly annoyed, annoyed or highly annoyed for a given vibration exposure. Further analysis of this extensive database of case studies, comprising vibration measurements and face-to-face interviews, will be extremely useful in developing research for the EU FP7

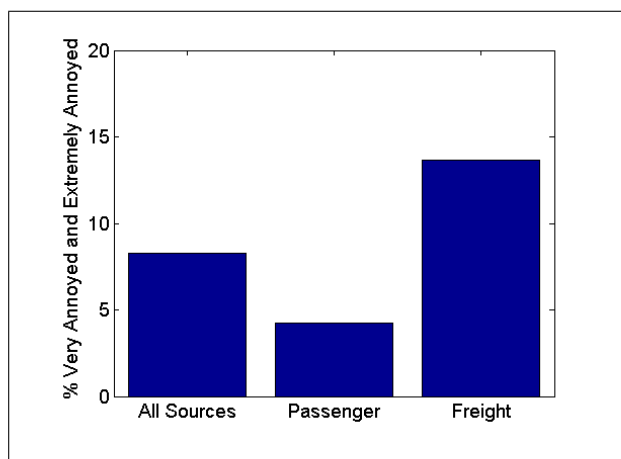


Figure 1. Percentage of respondents that were very annoyed or extremely annoyed by different railway vibration sources ( $N = 711$ )

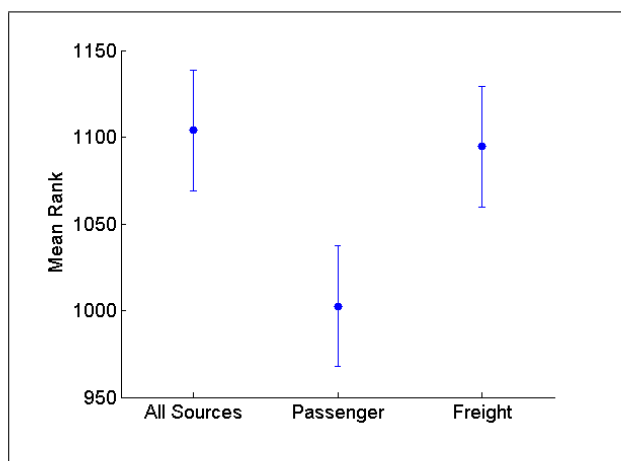


Figure 2. Multiple comparison of mean rank annoyance for different railway vibration sources ( $N = 711$ )

CargoVibes project, the aim of which is to facilitate the expansion of freight traffic on rail, whilst minimising detrimental effects on local residents [1]. However, vibration exposures were calculated for all railway traffic together and no attempt was made to differentiate between freight and passenger train exposure independently.

Figure 1 shows the percentage of respondents that stated they were either "very annoyed" or "extremely annoyed" by different railway vibration sources. In this case, all sources refers to freight and passenger railway sources, as well as other sources including maintenance cars. The higher percentage of annoyance caused by freight railway vibration suggests that people may respond differently to freight railway vibration than other railway vibration sources.

An initial Kruskal-Wallis test performed on the database of annoyance responses indicates that the annoyance response due to freight trains is significantly higher than that due to passenger trains ( $\chi^2 = 19.98, p < 0.001$ ). Figure 2 shows the mean rank of

annoyance scores for freight and passenger trains separately, along with their standard errors. The different mean ranks and non-overlapping standard errors indicate a significant difference in annoyance responses for freight and passenger train vibration sources. This gives confidence that exposure-response curves for annoyance may be distinctly different when passenger and freight train sources are considered independently.

It would therefore be beneficial to be able to identify freight train signals in the Defra database, and determine an exposure-response relationship specific to freight train vibration, so that the effect of an increase in vibration due to freight traffic can be better understood. The objectives of the current research are therefore to use an algorithm which separates unknown train vibration signals into passenger and freight train categories, in order to determine exposure-response relationships that are specific to freight and passenger train exposures separately.

## 2. Determining Vibration Exposure

Data in this paper is taken from existing measurements performed as part of the Defra funded research project "NANR209: Human Response to Vibration in Residential Environments" [6]. The vibration measurement protocol for this research project involved long term vibration monitoring at external positions, combined with time synchronised short term measurements taken inside dwellings located within 100 m of the relevant railway lines. The transmissibility calculated between these measurement pairs allowed the estimation of 24-hour vibration time histories within dwellings to be estimated.

The vibration measurements were performed in the field using Guralp CMG-5TD strong motion accelerometers with a 100 Hz low pass filter. While the internal measurements were being taken, the operators noted any train passes that occurred during the measurement period on a handwritten log. In most cases the time of the event pass-by, and the type of train, were noted.

Using this approach, 149 long term measurements were made, along with 522 short term internal measurements, allowing the estimation of 24-hour vibration time histories within 711 dwellings in the North West and Midlands regions of England.

In terms of quantifying the 24-hour vibration exposures, several different vibration descriptors were investigated, including the root mean square of the signal, the equivalent vibration level ( $L_{eq}$ ), the vibration exposure level ( $L_E$ ) and the vibration dose value ( $VDV$ ). It was discovered that the different vibration descriptors investigated all correlated well with each other, suggesting that, for the vibration exposures in this database, the type of averaging is largely unimportant. In addition, it was found that the application

of appropriate frequency weightings suggested in BS 6472-1:2008 [7] and ISO 2631-1:1997 [8] resulted in an improvement of the Spearman's correlation coefficient against the relevant annoyance responses. For these reasons, and to maintain consistency with previous work [6], the descriptor used to quantify the vibration exposures in this paper will be as described in BS 6472-1:2008 [7] ( $VDV$  using  $W_b$  weighting in the vertical axis).  $VDV$  is calculated as follows:

$$VDV = \sqrt[4]{\frac{T}{N} \sum_{n=1}^N x(n)^4} \quad (1)$$

where  $x(n)$  is the acceleration time history,  $T$  is the event duration in seconds and  $N$  is the number of samples.

### 3. Determining Annoyance Response

As well as estimations of vibration exposures, for each of the 711 dwellings, response data were collected by means of face-to-face interviews [6]. These interviews took the form of a neighbourhood satisfaction questionnaire, and gathered information on annoyance caused by vibration from different sources of railway traffic (passenger, freight, maintenance and all sources) among other things. For example, the interviewees were asked “...how bothered, annoyed or disturbed have you been by feeling vibration or hearing things rattle, vibrate or shake caused by [source]” and their responses were recorded on 5 point semantic scales and 11 point numeric scales as per ISO/TS 15666:2003 [9]. The results of the above question, where the source is either passing freight trains or passing passenger trains, were utilised in determining exposure-response relationships in this paper.

### 4. Separating Freight and Passenger Train Signals Using the Categorisation Algorithm

A binary probit model categorisation algorithm was applied to the train vibration signals in the Defra database, sorting the unknown train vibration signals into passenger and freight train categories. The creation of the algorithm, and an investigation into its accuracy, has been discussed in detail in a previous conference paper [10]. Although two different categorisation algorithms were discussed in this paper, only the binary probit model algorithm will be used in this research, since it was shown to have a higher accuracy of correct categorisation ( $79 \pm 7\%$ ).

The categorisation algorithm uses a training/testing method, whereby the algorithm calculates signal properties of known vibration event signals in a training data set, and then calculates the same

signal properties of unknown event signals in a data set to be tested. Finally the algorithm sorts the unknown event signals in the testing data set into passenger and freight train categories by comparing their signal properties to those of known passenger and freight train signals that make up the training data set. In this case, the training data set of known vibration event signals is taken from the short term vibration measurements during which the operators noted the type of each train pass-by that occurred during the measurement period.

The signal properties that are used in this algorithm are those that have been shown to be statistically significantly different at the 95% confidence interval and include the 3 dB and 10 dB envelope lengths (dB re  $1 \times 10^{-6} \text{ ms}^{-2}$ ), the  $L_E$ , the  $VDV$ , the Kurtosis in the time domain and the standard deviation, Kurtosis and Skewness in the frequency domain. The majority of the differences between freight and passenger train vibration signals are due to their differing event duration and frequency content, since freight trains tend to have longer pass-bys and different frequency content than passenger trains [6].

The algorithm works by calculating a binary probit model for each of the differentiating signal properties from the training set of known vibration signals. The binary probit model allows the regression of a continuous independent variable on a binary dependent variable to be calculated. For this application, the continuous variable is one of the differentiating signal properties calculated for each vibration event signal, and the binary variable is whether the signal comes from a passenger train (0) or a freight train (1). Individual signal properties for each tested vibration signal are then categorised as being more like freight train signal properties or passenger train signal properties based on their position on the binary probit curve. Finally, each tested vibration event signal is categorised as a freight train or a passenger train event depending on how many of its signal properties are deemed to be more similar to freight train signal properties, as determined by the binary probit model.

### 5. The Exposure-Response Model

Once the vibration signals had been sorted into freight and passenger train categories, it was possible to calculate exposure-response relationships for both categories, using an ordinal probit model with fixed thresholds. The statistical model used to formulate these exposure-response relationships is based upon one presented by Groothuis-Oudshoorn & Miedema [11]. For the data collected during the Defra funded project, self reported annoyance ( $A_i$ ) was recorded on an ordinal scale with  $J$  categories. It was assumed that a latent variable  $A^*$ , a linear combination of vi-

bration exposure ( $X$ ) and a random error component  $\varepsilon$  underlies the categorical annoyance variable  $A$ .

$$A_i^* = \mathbf{X}_i \mathbf{B} + \varepsilon \quad (2)$$

where  $\mathbf{B}$  is a vector of estimated parameters. The latent variable  $A^*$  is linked to the observed variable  $A_i$  by the relationship described in Equation 3, limiting its potential values between 0 and 100.

$$A_i = \begin{cases} 0 & \text{if } A_i^* < 0 \\ A_i^* & \text{if } A_i^* \in [0, 100] \\ 100 & \text{if } A_i^* > 100 \end{cases} \quad (3)$$

Previous exposure-response relationships have been determined by defining annoyance by the proportion of people that respond with annoyance above a certain level,  $C$  [11]. Three commonly used values of  $C$  are  $C = 28$  (percent slightly annoyed),  $C = 50$  (percent annoyed) and  $C = 72$  (percent highly annoyed). Thus, the probability that an individual exposed to a certain vibration exposure magnitude ( $V$ ) will respond with an annoyance level that is above a cut-off  $C$  can be expressed using Eq 4.

$$\begin{aligned} p_c(V) &= \text{Prob}(A^* \geq C) \\ &= \text{Prob}(\mathbf{X}\mathbf{B} + \varepsilon \geq C) \\ &= \text{Prob}(\varepsilon \geq C - \mathbf{X}\mathbf{B}) \end{aligned} \quad (4)$$

Assuming that the error term  $\varepsilon$  is normally distributed:

$$p_c(V) = \text{Prob}\left(1 - \Phi\left[\frac{C - \mathbf{X}\mathbf{B}}{\sigma}\right]\right) \quad (5)$$

where  $\Phi$  is cumulative normal distribution function and  $\sigma$  is the standard error. The distribution of responses at different annoyance levels can be expressed by altering the cut-off value,  $C$ .

## 6. Exposure-Response Relationships for Freight and Passenger Trains Independently

Using the exposure-response model described above, and the 24-hour VDV values calculated from train event signals separated into passenger and freight train categories using the categorisation algorithm, preliminary exposure-response curves for separate sources were developed. Figure 3 shows the exposure-response curves for separate sources, showing the curves for percent slightly annoyed (%SA), percent annoyed (%A) and percent highly annoyed (%HA). These exposure-response curves indicate that, for a

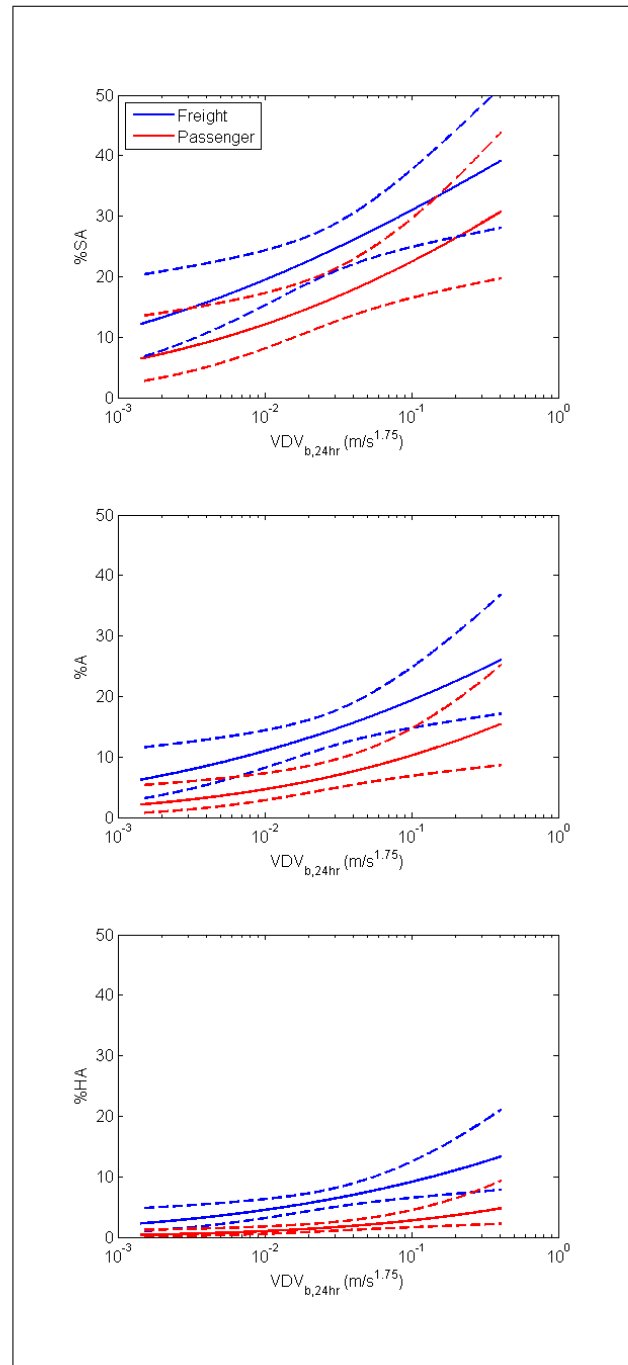


Figure 3. Preliminary exposure-response relationships for annoyance caused by exposure to railway and freight train vibration, with the 95% confidence intervals indicated by broken lines ( $N = 711$ )

given  $VDV$ , exposure to freight trains gives a significantly higher annoyance response than exposure to passenger trains. Note that these are only preliminary results, due to the fact that the categorisation algorithm is only able to correctly categorise freight and passenger trains to an accuracy of 79%.

The higher annoyance responses could be caused by several factors. Previous research has indicated that freight train vibration signals exhibit several differ-

ent signal properties to passenger trains, mainly due to their increased duration, resulting in longer envelope lengths, higher vibration dose values and higher vibration exposure levels [10].

The increased annoyance may also be due to the times of day in which freight trains are more prevalent. Previous research has indicated that people are more annoyed by the same magnitude of vibration exposure during night time hours (23:00 - 07:00) than during evening time hours (19:00 - 23:00) and more annoyed during evening time hours than during day time hours (07:00 - 19:00) [5]. The proportion of freight train pass-bys was found to increase gradually throughout these time periods, with the median proportion of freight railway traffic being 13%, 14% and 17% during day, evening and night time hours respectively. The higher proportion of freight traffic during the night, during which period people have been shown to be more annoyed by vibration, may therefore account for the increased annoyance responses observed for freight traffic.

## 7. Validity of Exposure-Response Curves

Although the categorisation algorithm was able to sort the unknown train vibration signals into freight and passenger train categories, the accuracy of this categorisation algorithm is only 79% ( $\pm 7\%$ ), and so the exposure-response curves developed using these separated signals can only be taken as preliminary results. For a small number of case studies, the categorisation algorithm predicts an unrealistically high proportion of freight train traffic, suggesting that the limited accuracy of the algorithm may cause it to be slightly over-sensitive when categorising a vibration signal as a freight train vibration signal.

Despite its somewhat limited accuracy, the correlation between the annoyance responses and the vibration exposures for different sources and the vibration exposures calculated using the categorisation algorithm is significant. The Spearman's correlation coefficient was calculated for pairs of exposures and responses and is shown in Table I. The correlation coefficients are higher, and the  $p$ -values more significant, when the passenger and freight exposures are paired with the response to passenger and freight respectively. This gives confidence that the algorithm is correctly separating freight and passenger train signals to a reasonably high level of accuracy.

## 8. Conclusions

The categorisation algorithm has successfully separated freight and passenger train signals into independent categories so that preliminary exposure-response curves can be derived for these sources separately. The

Table I. Spearman's Correlation Coefficient for different exposure-response pairs.

\* Not Significant \*\*  $p < 0.05$  \*\*\*  $p < 0.01$

	Response to Passenger	Response to Freight	Response to All Sources
Passenger Exposure	0.1044***	0.0853**	0.0667*
Freight Exposure	0.0676*	0.0992***	0.0626*

Spearman's correlation coefficient between the separate exposures and responses suggest that the algorithm separates the signals with a reasonably high degree of accuracy. However, the proportion of freight train pass-bys for a small number of case studies is unrealistically high, suggesting that the algorithm may be slightly over-sensitive in categorising vibration signals as freight train signals. Further research in this area could result in an increase in the accuracy and applicability of the categorisation algorithm, leading to potentially highly accurate exposure-response curves for passenger and freight railway vibration. This will be extremely beneficial in furthering the understanding of the human response to railway vibration, and the results will be relevant to research which aims to facilitate the expansion of freight traffic on rail, such as the CargoVibes project.

## Acknowledgement

Work presented in this paper is part of the research performed by the University of Salford and funded by the Department for Environment, Food and Rural Affairs (UK) and EU FP7 through the CargoVibes project.

## References

- [1] CargoVibes: Project Overview. CargoVibes. URL: <http://www.cargovibes.eu/?CategoryID=155&ArticleID=92>. Accessed April 2012.
- [2] H. M. E. Miedema, H. Vos: Exposure-response relationships for transport noise. *J. Acoust. Soc. Am.* **104**(6) (1998) 3432-3445.
- [3] R. Klæboe, I. H. Turunen-Rise, L. Hårvik, C. Madshus: Vibration in dwellings from road and rail traffic - part II: Exposure-effect relationships based on ordinal logit and logistic regression models. *Appl. Acoust.* **64** (2003) 89-109.
- [4] E. Öhström: Effects of exposure to railway noise - a comparison between areas with and without vibration. *J. Sound. Vib.* **205**(4) (1997) 555-560.
- [5] E. Peris, J. Woodcock, G. Sica, A. T. Moorhouse, D. C. Waddington: Annoyance due to railway vibration at different times of the day. *J. Acoust. Soc. Am.* **131**(2) (2012) EL191-EL196.
- [6] D. C. Waddington, A. T. Moorhouse, A. Steele, J. Woodcock, J. Condie, E. Peris, G. Sica, Z. Koziel: Human response to vibration in residential environments (NANR209), Final project report. Defra, London, 2011.

- [7] British Standards Institution: Guide to evaluation of human exposure to vibration in buildings, part 1: vibration sources other than blasting. BS6472-1:2008, London, 2008.
- [8] International Organization for Standardization: Mechanical vibration and shock - Evaluation of human exposure to whole-body vibration - Part 1: General requirements. ISO 2631-1:1997, Geneva, 1997.
- [9] International Organization for Standardization: Acoustics - assessment of noise annoyance by means of social and socio-acoustic surveys. ISO/TS 15666:2003, Geneva, 2003.
- [10] C. J. Sharp, D. C. Waddington, J. Woodcock, G. Sica, E. Peris, A. T. Moorhouse: Two algorithms for the sorting of unknown train vibration signals into freight and passenger train categories. Proc. Acoustics 2012
- [11] C. G. M. Groothuis-Oudshoorn, H. M. E. Miedema: Multilevel grouped regression for analyzing self-reported health in relation to environmental factors: the model and its application. Biometrical J. **48(1)** (2006) 67-82.